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ARTIFICIAL INTELLIGENCE AND LAW: AN OVERVIEW

Harry Surden*

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INTRODUCTION

Much has been written recently about artificial intelligence (AI) and law.¹ But what is AI, and what is its relation to the practice and administration of law? This article addresses those questions by providing a high-level overview of AI and its use within law. The discussion aims to be nuanced but also understandable to those without a technical background. To that end, I first discuss AI generally. I then turn to AI and how it is being used by lawyers in the practice of law, people and companies who are governed by the law, and government officials who administer the law.

A key motivation in writing this article is to provide a realistic, demystified view of AI that is rooted in the actual capabilities of the technology. This is meant to contrast with discussions about AI and law that are decidedly futurist in nature. That body of work speculates about the effects of AI developments that do not currently exist and which may, or may not, ever come about.² Although those futurist conversations have their place, it is important to acknowledge that they involve significant, sometimes unsupported, assumptions about where the technology is headed. That speculative discussion often distracts from the important, but perhaps less exotic, law and policy issues actually raised by AI technology today.³

1. See generally Sonia K. Katyal, *Private Accountability in the Age of Artificial Intelligence*, 66 UCLA L. REV. 54 (2019); Frank Pasquale, *A Rule of Persons, Not Machines: The Limits of Legal Automation*, 87 GEO. WASH. L. REV. 1 (2019).

2. Pasquale, *supra* note 1, at 3–4.

3. My belief is that AI law and policy discussions are generally better served by focusing on the current and likely near-term (e.g., no more than five years out) capabilities of AI technology, rather than speculating about long-term or futuristic AI developments, which may or may not arise or which may arise in different or unpredictable ways. Although we might make reasonable predictions about the direction of technology a few (e.g., five) years out, most authors (including this one) are not really very good about reliably predicting the direction of technology more than a few years out. Those speculative discussions sometimes provide a misleading and exaggerated view of the current capabilities of technology. Finally, they often distract policymakers toward speculative problems of the future and ignore more pressing and realistic problems that exist today.

I. *What is AI?*

What is AI? There are many ways to answer this question, but one place to begin is to consider the types of problems that AI technology is often used to address. In that spirit, we might describe AI as using technology to automate tasks that “normally require human intelligence.”⁴ This description of AI emphasizes that the technology is often focused upon automating specific types of tasks: those that are thought to involve intelligence when people perform them.⁵

A few examples will help illustrate this depiction of AI. Researchers have successfully applied AI technology to automate some complex activities, including playing chess, translating languages, and driving vehicles.⁶ What makes these AI tasks rather than automation tasks generally? It is because they all share a common feature: when *people* perform these activities, they use various higher-order cognitive processes associated with human intelligence.

For instance, when humans play chess, they employ a range of cognitive capabilities, including reasoning, strategizing, planning, and decision-making.⁷ Similarly, when people translate from one language to another, they activate higher-order brain centers for processing symbols, context, language, and meaning.⁸ Finally, when people drive automobiles, they engage a variety of brain systems, including those associated with vision, spatial recognition, situational awareness, movement, and judgment.⁹ In short, when engineers automate an activity that requires cognitive activity when performed

4. *Artificial Intelligence*, ENG. OXFORD LIVING DICTIONARIES, https://en.oxforddictionaries.com/definition/artificial_intelligence [<https://perma.cc/WF9V-YM7C>] (last visited Feb. 27, 2019); see STUART J. RUSSELL & PETER NORVIG, *ARTIFICIAL INTELLIGENCE: A MODERN APPROACH* 1 (3rd ed. 2010).

5. RUSSELL & NORVIG, *supra* note 4, at 1. Let’s put aside, for the purposes of this discussion, the considerable diverse range of views about what human “intelligence” is or how that word should be defined.

6. *Id.* at 1, 21.

7. J.M. Unterrainer et al., *Planning Abilities and Chess: A Comparison of Chess and Non-Chess Players on the Tower of London Task*, 97 BRIT. J. PSYCHOL. 299, 299–300, 302 (2006).

8. RUSSELL & NORVIG, *supra* note 4, at 21.

9. Shunichi Doi, *Technological Development of Driving Support Systems Based on Human Behavioral Characteristics*, 30 IATSS RES. 19, 20–21 (2006).

by humans, it is common to describe this as an application of AI.¹⁰ This definition, though not fully descriptive of all AI activities, is nonetheless helpful as a working depiction.¹¹

A. Today's AI is Not Actually Intelligent

Now that we have a broad description of what AI is, it is also important to understand what today's AI technology is not. When many people hear the term "AI" they imagine current AI systems as thinking machines.¹² A common misperception along this line is that existing AI systems are producing their results by engaging in some sort of synthetic computer cognition that matches or surpasses human-level thinking.¹³

The reality is that today's AI systems are decidedly not intelligent thinking machines in any meaningful sense. Rather, as I discuss later, AI systems are often able to produce useful, intelligent results without intelligence. These systems do this largely through heuristics—by detecting patterns in data and using knowledge, rules, and information that have been specifically encoded by people into forms that can be processed by computers.¹⁴ Through these computational approximations, AI systems often can produce surprisingly good results on certain complex tasks that, when done by humans, require cognition. Notably, however, these AI systems do so by using computational mechanisms that do not resemble or match human thinking.¹⁵

By contrast, the vision of AI as involving thinking machines with abilities that meet or surpass human-level cognition—often referred

10. RUSSELL & NORVIG, *supra* note 4, at 2.

11. One reason that this characterization of AI is not fully descriptive is that AI has been used to do many activities that humans cannot do. For example, AI technology has been used to spot credit card fraud among billions of transactions using statistical probabilities. *See id.* at 1034. If we frame AI as engaging in activities that require human intelligence, we may miss the group of activities that have been automated that humans cannot actually do due to our cognitive limitations. Those issues aside, the working definition that we have here, albeit not complete, is sufficient for our discussion.

12. Harry Surden, *Machine Learning and Law*, 89 WASH. L. REV. 87, 89 (2014).

13. *Id.* This exaggerated view of AI has been promoted by companies advertising "cognitive computing," the media, and various projects that provide a misleading view of the state of AI. *Id.*

14. *Id.* at 89–90.

15. *Id.* at 87.

to as Strong AI or Artificial General Intelligence (AGI)—is only aspirational.¹⁶ That is the fictional depiction of AI in the entertainment industry in which computers can engage in arbitrary conversation about abstract topics, such as philosophy, and operate as fully independent cognitive systems.¹⁷ Although Strong AI has long been a goal of research efforts, even the most state-of-the-art AI technology does not meaningfully resemble Artificial General Intelligence.¹⁸ Today's AI systems cannot, nor are they necessarily designed to, match higher-order human abilities, such as abstract reasoning, concept comprehension, flexible understanding, general problem-solving skills, and the broad spectrum of other functions that are associated with human intelligence.¹⁹ Instead, today's AI systems excel in narrow, limited settings, like chess, that have particular characteristics—often where there are clear right or wrong answers, where there are discernible underlying patterns and structures, and where fast search and computation provides advantages over human cognition.²⁰

Though it is certainly possible that Strong AI will one day come about (although many experts in the field are skeptical), at a minimum, it is this author's opinion that there is little actual evidence that suggests that we are close to such a development in the near-term time frame (e.g., five to ten years). To that end, this article's

16. Terence Mills, *AI vs AGI: What's the Difference?*, FORBES (Sept. 17, 2018, 7:00 AM), <https://www.forbes.com/sites/forbestechcouncil/2018/09/17/ai-vs-agi-whats-the-difference/#517ec50d38ee> [<https://perma.cc/DU7G-LY8C>].

17. Bilge Ebiri, *The 15 Best Robot Movies of All Time*, VULTURE (Mar. 6, 2015), <https://www.vulture.com/2015/03/15-best-robot-movies-of-all-time.html> [<https://perma.cc/MGP7-922A>].

18. Mills, *supra* note 16.

19. Jack Krupansky, *Untangling the Definitions of Artificial Intelligence, Machine Intelligence, and Machine Learning*, MEDIUM (June 13, 2017), <https://medium.com/@jackkrupansky/untangling-the-definitions-of-artificial-intelligence-machine-intelligence-and-machine-learning-7244882f04c7> [<https://perma.cc/RVZ4-88NP>].

20. John Rennie, *How IBM's Watson Computer Excels at Jeopardy!*, PLOS BLOGS (Feb. 14, 2011), <https://blogs.plos.org/retort/2011/02/14/how-ibm%E2%80%99s-watson-computer-will-excel-at-jeopardy/> [<https://perma.cc/3RS8-K2KU>]. The ability of today's AI to excel in specific, constrained, well-defined areas is sometimes referred to as "narrow" intelligence. Rajiv Desai, *Artificial Intelligence (AI)*, DR RAJIV DESAI: AN EDUC. BLOG (Mar. 23, 2017), <http://drrajivdesaimd.com/2017/03/23/artificial-intelligence-ai/> [<https://perma.cc/BR7M-ZJFM>].

discussion refrains from speculation about future developments and is instead focused on the current state of AI technology.²¹

B. AI by the Technology

A different approach to understanding AI is to examine, not the problems it can or cannot solve, but instead the research and technology from the discipline. At a high level, AI is generally considered a subfield of computer science.²² However, AI is truly an interdisciplinary enterprise that incorporates ideas, techniques, and researchers from multiple fields, including statistics, linguistics, robotics, electrical engineering, mathematics, neuroscience, economics, logic, and philosophy, to name just a few.²³ Moving one level lower, AI can be thought of as a collection of technologies that have emerged from academic and private-sector research. We can therefore gain a more useful view of AI by better understanding the underlying technologies that enable it.

So, what mechanisms allow AI to actually automate tasks such as playing chess, translating languages, or driving cars? Today, most successful artificial technological approaches fall into two broad categories: (1) machine learning and (2) logical rules and knowledge representation.²⁴ Let's look at each of these methods in more detail.

21. See *infra* Part I.C. Another point is that when AI is used to address a complex task, such as playing chess or driving a car, it uses computer-based methods that look quite different from the way humans are thought to solve these tasks. See Surden *supra* note 12, at 88; Rennie, *supra* note 20.

22. Bernard Marr, *The Key Definitions of Artificial Intelligence (AI) That Explain Its Importance*, FORBES (Feb. 14, 2018, 1:27 AM), <https://www.forbes.com/sites/bernardmarr/2018/02/14/the-key-definitions-of-artificial-intelligence-ai-that-explain-its-importance/#1424d87d4f5d> [https://perma.cc/T2HU-9ZPF].

23. Desai, *supra* note 20.

24. See generally Rene Buest, *Artificial Intelligence Is About Machine Reasoning—or When Machine Learning Is Just a Fancy Plugin*, CIO (Nov. 3, 2017, 7:06 AM), <https://www.cio.com/article/3236030/artificial-intelligence-is-about-machine-reasoning-or-when-machine-learning-is-just-a-fancy-plugin.html> [https://perma.cc/Z88C-ZJA4] (explaining the progress of artificial intelligence and machine ability to learn reasoning skills).

1. *Machine Learning*

Machine learning refers to a family of AI techniques that share some common characteristics.²⁵ In essence, most machine-learning methods work by detecting useful patterns in large amounts of data.²⁶ These systems can then apply these patterns in various tasks, such as driving a car or detecting fraud, in ways that often produce useful, intelligent-seeming results.²⁷ Machine learning is not one approach but rather refers to a broad category of computer techniques that share these features.²⁸ Common machine-learning techniques that readers may have heard of include neural networks/deep learning, naive Bayes classifier, logistic regression, and random forests.²⁹ Because machine learning is the predominant approach in AI today, I spend a little more time focused upon machine learning.

At the outset, it is important to clarify the meaning of the word learning in machine learning. Based upon the name, one might assume that these systems are learning in the way that humans do. But that is not the case. Rather, the word learning is used only as a rough metaphor for human learning. For instance, when humans learn, we often measure progress in a functional sense—whether a person is getting better at a particular task over time through experience. Similarly, we can roughly characterize machine-learning systems as functionally “learning” in the sense that they too can improve their performance on particular tasks over time.³⁰ They do this by examining more data and looking for additional patterns.³¹

25. David Fumo, *Types of Machine Learning Algorithms You Should Know*, TOWARDS DATA SCIENCE (June 15, 2017), <https://towardsdatascience.com/types-of-machine-learning-algorithms-you-should-know-953a08248861> [<https://perma.cc/3QQU-6LXT>].

26. *What Is Machine Learning? 3 Things You Need to Know*, MATHWORKS: MACHINE LEARNING, <https://www.mathworks.com/discovery/machine-learning.html> [<https://perma.cc/F45M-DTMD>] (last visited Mar. 13, 2019).

27. Bernard Marr, *The Top 10 AI and Machine Learning Use Cases Everyone Should Know About*, FORBES (Sept. 30, 2016, 2:17 AM), <https://www.forbes.com/sites/bernardmarr/2016/09/30/what-are-the-top-10-use-cases-for-machine-learning-and-ai/#e19355a94c90> [<https://perma.cc/ADN8-A5Z5>].

28. MATHWORKS, *supra* note 26.

29. Mandeep Sidana, *Types of Classification Algorithms in Machine Learning*, MEDIUM (Feb. 28, 2017), <https://medium.com/@Mandysidana/machine-learning-types-of-classification-9497bd4f2e14> [<https://perma.cc/84UE-AR2R>].

30. MATHWORKS, *supra* note 26.

31. *Id.*

Importantly, the word learning does not imply that these systems are artificially replicating the higher-order neural systems found in human learning. Rather, these algorithms improve their performance by examining more data and detecting additional patterns in that data that assist in making better automated decisions.³²

Let us aim to get an intuitive sense as to how machine-learning systems use patterns in data to produce intelligent results. Consider a typical e-mail spam filter. Most e-mail software uses machine learning to automatically detect incoming spam e-mails (i.e. unwanted, unsolicited commercial e-mails) and divert them into a separate spam folder.³³

How does such a machine-learning system automatically identify spam? Often the key is to “train” the system by giving it multiple examples of spam e-mails and multiple examples of “wanted” e-mails.³⁴ The machine-learning software can then detect patterns across these example e-mails that it can later use to determine the likelihood that a new incoming e-mail is either spam or wanted.³⁵ For instance, when a new e-mail arrives, users are usually given the option to mark the e-mail as spam or not.³⁶ Every time users mark an e-mail as spam, they are providing a training example for the system. This signals to the machine-learning software that this is a human-verified example of a spam e-mail that it should analyze for telltale patterns that might distinguish it from wanted e-mails.³⁷

32. *Id.*

33. See, e.g., *Customize Spam Filter Settings*, GOOGLE, <https://support.google.com/a/answer/2368132?hl=en> [<https://perma.cc/RW8F-G743>] (last visited Mar. 13, 2019); *Overview of the Junk Email Filter*, MICROSOFT, <https://support.office.com/en-us/article/overview-of-the-junk-email-filter-5ae3ea8e-cf41-4fa0-b02a-3b96e21de089> [<https://perma.cc/H4CX-U8UP>] (last visited Mar. 13, 2019).

34. MATHWORKS, *supra* note 27.

35. *Comparison of Machine Learning Methods in Email Spam Detection*, MATHIAS SCHILLING: BLOG (Feb. 11, 2018), <https://www.matchilling.com/comparison-of-machine-learning-methods-in-email-spam-detection/> [<https://perma.cc/HW9W-JJ8U>].

36. Nicholas Moline, *Combatting Spam Emails and Contact Forms*, JUSTIA LEGAL MARKETING & TECH. BLOG (Dec. 4, 2018), <https://onward.justia.com/2018/12/04/combatting-spam-emails-and-contact-forms/> [<https://perma.cc/PTV2-BN3X>].

37. Surden, *supra* note 12, at 90–91.

What might such a useful pattern look like? One common approach simply uses word probabilities.³⁸ In that technique, the system attempts to detect words and phrases that are more likely than average to appear in a spam e-mail. For instance, let's imagine that a user has marked 100 e-mails as spam. Say that the machine-learning algorithm examines all of these e-mails and keeps track of the rate at which certain words appear in spam e-mails versus wanted e-mails. Let's imagine that the system finds the following pattern: of e-mails that contain the word "free," 80% of those are spam e-mails, and only 20% of them are wanted e-mails (compared with a 5% spam-rate generally). The machine-learning algorithm has just detected a useful pattern—the presence of a particular word, "free," in an e-mail is a signal that this e-mail is much more likely than average (80% versus 5%) to be spam.

The machine-learning system can now use this pattern to make reasonable, automated decisions in spam-filtering going forward. The next time an e-mail comes in with the word "free" in it, the system is going to determine that this e-mail has a high probability of being spam and will automatically divert that e-mail to the spam folder. We can think of this as an intelligent result because this is roughly what a person would have done had he quickly scanned the e-mail, noticed words such as "free," and decided it was spam. In sum, in the above example, the system automatically learned, by looking for patterns among earlier spam e-mail data, that the word "free" is a statistical indicator that an incoming e-mail is likely spam.

As suggested, machine-learning systems are designed to learn and improve over time. How do they get better at identifying spam? By examining more data and looking for more useful signals of spam. For instance, imagine further that the user marks 100 additional e-mails as spam. By examining that trove of e-mails, the software may learn a second correlation on its own: that e-mails originating from the country Belarus are much more likely to be spam than

38. *Introduction to Bayesian Filtering*, PROCESS SOFTWARE, http://www.process.com/products/pmas/whitepapers/intro_bayesian_filtering.html [<https://perma.cc/7S8L-EG3S>] (last visited Mar. 13, 2019).

e-mails originating from elsewhere. The system has learned an additional signal for the likelihood of spam that should make its filtering better. With two signals—“free” and origination from Belarus—the e-mail system now has a better suite of spam-indicating patterns than it did before. When a future e-mail comes in with either the word “free” or origination from Belarus, the system will be able to mark it as spam with a high degree of probability.

This example illustrates a few points about machine learning more broadly. First, it shows how software can learn a useful pattern on its own without having a programmer explicitly program that pattern ahead of time.³⁹ In our example, the software learned the rule that the presence of the word “free” was a likely indicator for spam on its own because its algorithm was specifically designed to identify words that are correlated with spam and calculate the associated probabilities. In other words, no programmer had to manually instruct the software that a word like “free” was a likely indicator of spam; rather, the machine-learning software determined it automatically by calculating the words most frequently associated with spam.⁴⁰ Thus, machine-learning algorithms are, in some sense, able to program themselves because they have the capability of detecting useful decision rules on their own as they examine data and detect statistical outliers, rather than having those rules laid out for them explicitly, ahead of time, by human programmers.

Second, this example illustrates that the software was learning by improving its performance over time with more data.⁴¹ At first, the software had detected only one indicia of spam—the presence of the word “free, but over time it figured out another spam signal—e-mails originating from Belarus. In that way, the software acquired more heuristics by examining more data that made it better at automatically detecting spam e-mails than it was before. This illustrates how the “learning” in machine learning is merely a metaphor for human learning and does not involve replicating the higher-order brain and

39. Surden, *supra* note 12, at 91.

40. *Id.*

41. *Id.* at 92.

cognitive processes found in human learning, but rather, involves the detection of additional useful patterns with more data.⁴²

This example also helps us understand the limits of machine learning compared to human intelligence and Strong AI. When a human reads an e-mail and decides that it is spam, the person understands its words and their meaning by activating higher-order cognitive centers associated with language. This might happen very quickly, as a human decides whether, through meaning, that given e-mail is or is not spam. By contrast, in the machine-learning-based spam filter listed above, the system doesn't understand the meaning of words like "free" or the concept of countries like Belarus, nor does it need to.⁴³ Rather, the machine-learning system described above made its automated decisions based upon heuristics—the presence of statistically relevant signals like "free"—to make its intelligent-seeming decisions.⁴⁴

What is interesting, and perhaps amazing, is that these patterns and heuristics can sometimes produce intelligent results—the same results that a human would have come to had she read it—without underlying human-level cognition. This is a fascinating fact—that machines can use detected patterns to make useful decisions about certain complex things without understanding their underlying meaning or significance in the way a human might. This observation will be relevant once we examine machine learning applied in the legal context and will be helpful in understanding the limits of AI in law.

In sum, machine learning is currently the most significant and impactful approach to artificial intelligence. It underlies most of the major AI systems impacting society today, including autonomous vehicles, predictive analytics, fraud detection, and much of automation in medicine.⁴⁵ It is important, however, to emphasize how dependent machine learning is upon the availability of data. The rise of machine learning has been fueled by a massive increase in the

42. *Id.* at 89.

43. *See id.*

44. Surden, *supra* note 12, at 91.

45. MATHWORKS, *supra* note 27.

availability of data on the Internet, as more societal processes and institutions operate using computers with stored, networked data.⁴⁶ Because effective machine learning typically depends upon large amounts of high-quality, structured, machine-processable data, machine-learning approaches often do not function well in environments where there is little data or poor-quality data.⁴⁷ As will be discussed later, law is one of those domains where high-quality, machine-processable data is currently comparatively scarce except in particular niches.

2. Rules, Logic, and Knowledge Representation

Let us now turn to the other major branch of AI: logical rules and knowledge representation.⁴⁸ The goal behind this area of AI is to model real-world phenomena or processes in a form that computers can use, typically for the purposes of automation.⁴⁹ Often this involves programmers providing a computer with a series of rules that represent the underlying logic and knowledge of whatever activity the programmers are trying to model and automate.⁵⁰ Because the knowledge rules are deliberately presented in the language of the computer, this allows the computer to process them and deductively reason about them.⁵¹

Knowledge representation has a long and distinguished history in the field of AI research and has contributed to many so-called expert systems.⁵² In an expert system, programmers in conjunction with experts in some field, such as medicine, aim to model that area of expertise in computer-understandable form. Typically, system designers try to translate the knowledge of experts into a series of formal rules and structures that a computer can process. Once created, such a medical-expert system might allow later users to

46. Desai, *supra* note 20.

47. *Id.*

48. Yoav Shoham, *Why Knowledge Representation Matters*, 59 COMM. ACM 47, 47–48 (2016).

49. Harry Surden, *The Variable Determinacy Thesis*, 12 COLUM. SCI. & TECH. L. REV. 1, 20 (2011).

50. *Id.*

51. *Id.* at 21–22.

52. See generally Richard E. Susskind, *Expert Systems in Law: A Jurisprudential Approach to Artificial Intelligence and Legal Reasoning*, 49 MOD. L. REV. 168 (1986).

make automated, expert-level diagnoses using the encoded knowledge (e.g., If patient has symptoms X and Y, the expert system, using its rules, determines that it is likely medical condition Z).

A good example of a legal-expert system comes from tax-preparation software such as TurboTax.⁵³ To create such a system, software developers, in consultation with tax attorneys and others experts in the personal income tax laws, translate the meaning and logic of tax provisions into a set of comparable formal rules that a computer can process.⁵⁴

Let us get an intuition as to what it actually means to “translate” a law into a computer rule. Imagine that there is a tax law that says that for every dollar of income that somebody makes over \$91,000, she will be taxed at a marginal tax rate of 28%. A programmer can take the logic of this legal provision and translate it into an if-then computer rule that faithfully represents the meaning of the law (e.g., If income > 91,000, then tax rate = 28%).⁵⁵ Once represented formally, the preparation software can use such a computer rule to analyze the income being reported by the filer and automatically apply the appropriate legal tax rate.⁵⁶ The same can occur with many other translated tax provisions. Although this is an over-simplified example, it illustrates the basic logic underlying the law-to-computer-rule translation process.

More broadly, these knowledge, logic, and rules-based AI methods involve a top-down approach to computation. This means that programmers must, ahead of time, explicitly provide the computer with all of its operating and decision rules. This is in contrast to the bottom-up machine-learning approach described earlier, where the computer algorithm organically determined its operating rules on its own.⁵⁷

53. Surden, *supra* note 50, at 78.

54. *Id.*

55. WARD FARNSWORTH, *THE LEGAL ANALYST: A TOOLKIT FOR THINKING ABOUT THE LAW* 164 (2007) (“Most laws—whether made by legislatures, courts, agencies, or anyone else—can be understood as if-then statements.”); Surden, *supra* note 50, at 23.

56. Surden, *supra* note 50, at 4.

57. *Id.* at 71–72.

There are a few points to note about these rules-based knowledge-representation systems. Although they have not made as large an impact as machine-learning systems, there is a power to this explicit, top-down knowledge representation. Once rules are represented in a computer-programming language, a computer can manipulate these rules in deductive chains to come to nonobvious conclusions about the world.⁵⁸ These systems can combine facts about the world, using logical rules, to alert users about things that might be too difficult for a person to figure out on her own.⁵⁹ Additionally, knowledge-based AI systems can harness the power of computing to reveal hard-to-detect details—such as contradictions—embedded in systems that a human would not be able to discern.⁶⁰

They can also engage in complex chains of computer reasoning that would be too difficult for a human to do.⁶¹ Take an example from the tax context. During the course of work, one might have a separate credit card used for business trips. The income tax code often treats business expenses different than personal expenses.⁶² The computer could be programmed with a rule indicating that expenses on a particular credit card should be marked as business expenses. Having programmed a rule about differential treatment for business expenses, the computer could automatically treat thousands of expenses differently using the tax-treatment rule.⁶³ The point is that knowledge and rules-based AI systems, in the right setting, can be very powerful tools. Knowledge-based expert systems and other policy-management systems are very widespread in the business world.⁶⁴

58. *Id.* at 21–22.

59. *Id.*

60. See Marie-Catherine de Marneffe et al., *Finding Contradictions in Text*, in 46TH ANNUAL MEETING OF THE ASSOCIATION FOR COMPUTATIONAL LINGUISTICS: HUMAN LANGUAGE TECHNOLOGIES 1039, 1039 (2008).

61. See, e.g., Matthew Hutson, *Computers Are Starting to Reason Like Humans*, SCI. (June 14, 2017, 4:00 PM), <http://www.sciencemag.org/news/2017/06/computers-are-starting-reason-humans> [<https://perma.cc/XG5K-29TE>].

62. Compare 26 U.S.C. § 262 (2018) (detailing federal tax laws for “[p]ersonal, living, and family expenses”), with 26 U.S.C. § 162 (2018) (detailing federal tax laws for “[t]rade or business expenses”).

63. Michael Shehab, *How AI Impacts the Tax Function*, CFO (Sept. 27, 2017), <http://www.cfo.com/tax/2017/09/ai-impacts-tax-function/> [<https://perma.cc/QE7J-KKW5>].

64. Priti Srinivas Sajja & Rajendra Akerkar, *Knowledge-Based Systems for Development*, in

3. *Hybrid AI Systems*

The prior section indicated that there are, at a high level, two broad ways to program computer systems to do AI tasks. The first approach involves machine learning, where systems rely upon algorithms that detect patterns in data that can be harnessed to make intelligent decisions.⁶⁵ The second approach involves knowledge representation and logic rules, in which explicit facts and rules about some activity are explicitly programmed into software, harnessing the knowledge of domain experts about how some system or activity operates.⁶⁶ Both AI approaches can be effective depending on their own domain. This section examines various ways in which AI systems are actually combinations of multiple techniques.

a. Machine Learning / Knowledge Representation Hybrid Systems

One point to emphasize is that many modern AI systems are not fully machine-learning or knowledge-based systems but are instead hybrids of these two approaches.⁶⁷ For example, self-driving cars operate using trained machine-learning systems that help them drive. The system learns to drive itself through a repeated training process by which it automatically infers appropriate driving behavior.⁶⁸ However, a good deal of the behavior of the self-driving car also involves explicit rules and knowledge representation.⁶⁹ In many autonomous vehicles projects, humans have hand-coded a series of

ADVANCED KNOWLEDGE-BASED SYSTEMS: MODELS, APPLICATIONS AND RESEARCH 11 (Priti Srinivas Sajja & Rajendra Akerkar eds., 2010) (ebook).

65. PETER FLACH, MACHINE LEARNING: THE ART AND SCIENCE OF ALGORITHMS THAT MAKE SENSE OF DATA 3 (2012).

66. S.I. GASS ET AL., FEDERAL EMERGENCY MANAGEMENT AGENCY, EXPERT SYSTEMS AND EMERGENCY MANAGEMENT: AN ANNOTATED BIBLIOGRAPHY 22 (1986).

67. Clare Corthell, *Hybrid Intelligence: How Artificial Assistants Work*, MEDIUM (May 26, 2016), <https://medium.com/@clarecorthell/hybrid-artificial-intelligence-how-artificial-assistants-work-cefbafbd5334> [<https://perma.cc/BD66-NZ9B>].

68. Andrew Ng, *Autonomous Driving*, COURSERA, <https://www.coursera.org/learn/machine-learning/lecture/zYS8T/autonomous-driving> [<https://perma.cc/XX6W-M6BF>] (last visited Mar. 25, 2019) (video discussing training machine-learning algorithm to drive vehicle).

69. *Self-Driving Cars Explained*, UNION CONCERNED SCIENTISTS (Feb. 21, 2018), <https://www.ucsusa.org/clean-vehicles/how-self-driving-cars-work> [<https://perma.cc/57SC-3L3P>].

rules, based upon the knowledge of driving, that represent generally appropriate behavior.⁷⁰ For example, the behavior that one should generally stop at a stop sign is likely to be hand coded. In addition, human coders manually update features on maps, for example, identifying stop signs.⁷¹ So for an AI system as complex as a self-driving vehicle, it must rely upon a mix of AI technologies, including machine-learning models, as well as hand-coded knowledge-representation rules about the world. We can, therefore, think of it as a hybrid system. The larger point is that we need not think of AI systems as exclusively involving one approach or another, but rather often involves a mixture of the two.

b. Human–AI System Hybrids and Humans in the Loop

Another important point: many successful AI systems are not fully autonomous but rather involve hybrids of computer and human decision-making.⁷² A fully autonomous system is one that makes all important decisions about its own activity. By contrast, many leading AI systems are automatic to the extent that they are able but then occasionally will defer important decisions to humans. This system design is known as having “a human in the loop.”⁷³ When a system has a human in the loop, the system does its best to perform autonomously in conditions where it is able to do so. But the system will defer to a human to make a difficult judgment or an assessment that remains outside of the system’s capability or for which a computer decision is deemed societally inappropriate.

For example, one major problem in self-driving vehicles is often referred to as the long tail problem.⁷⁴ This refers to the idea that there

70. James Fell & James Hedlund, Book Review, 9 TRAFFIC INJ. PREVENTION 500, 500 (2008), <https://doi.org/10.1080/15389580802335273> [<https://perma.cc/A2B3-LNP7>].

71. Vikram Mahidhar & Thomas H. Davenport, *Why Companies That Wait to Adopt AI May Never Catch Up*, HARV. BUS. REV. (Dec. 6, 2018), <https://hbr.org/2018/12/why-companies-that-wait-to-adopt-ai-may-never-catch-up> [<https://perma.cc/7DBV-MHF3>].

72. Richard Waters, *Artificial Intelligence: When Humans Coexist with Robots*, FIN. TIMES (Oct. 9, 2018), <https://www.ft.com/content/bcd81a88-cadb-11e8-b276-b9069bde0956> [<https://perma.cc/ER7G-KRNE>].

73. *Id.*

74. Evan Ackerman, *Autonomous Vehicles vs. Kangaroos: The Long Furry Tail of Unlikely Events*, IEEE SPECTRUM (July 5, 2017, 1:30 PM), <https://spectrum.ieee.org/cars-that-think/transportation/self->

are so many different and unexpected circumstances that could happen when driving and that it is difficult to completely train a machine-learning system that can manage every circumstance.⁷⁵ For instance, if there is an accident blocking an entire road, a police vehicle may temporarily reroute vehicles onto a sidewalk. A self-driving vehicle driving autonomously may not know what to do in such a case. One popular approach in self-driving cars is known as remote assist.⁷⁶ When a self-driving vehicle encounters a situation where it doesn't know what to do, it can essentially call for help to a call center staffed by people.⁷⁷ There, humans can see what is going on through the self-driving car's sensors and figure out what to do.⁷⁸ They can, for instance, take remote control of the vehicle, steer it around the difficult situation, and then return it to autonomous mode once things look normal.⁷⁹ This is an example of a human in the loop, where a difficult situation beyond the capability of a self-driving vehicle is deferred to a human. The larger point is that many complex AI systems will not be fully autonomous, but rather may include humans in the loop for particularly difficult judgments or assessments beyond state-of-the-art AI. As I later discuss, partially autonomous, human-in-the-loop systems are common in the legal domain.

C. AI's Current Capabilities and Limits

Stepping back for a moment, we are now in a position to more realistically appreciate both the capabilities and limits of current AI technology. Understanding the technology also allows us to see why AI tends to be useful for certain types of tasks and not others. This is key because these same limitations apply in the context of law. We

driving/autonomous-cars-vs-kangaroos-the-long-furry-tail-of-unlikely-events [https://perma.cc/K2M9-F2GR].

75. *Id.*

76. Alex Davies, *Self-Driving Cars Have a Secret Weapon: Remote Control*, WIRED (Feb. 1, 2018, 7:00 AM), <https://www.wired.com/story/phantom-teleops/> [https://perma.cc/DKN7-UA7V].

77. *Id.*

78. *Id.*

79. *Id.*

want to be able to critically evaluate where AI is likely to impact law but also where it is less likely to have an impact.

In this regard, one must be careful when extrapolating to the future based upon current AI achievements. People occasionally assume that because AI has successfully automated one complex task—such as playing chess, driving, or learning how to play a video game—that it naturally can be used to automate nearly any other type of complex task.⁸⁰ However, existing AI tends to be “narrow” intelligence—systems narrowly tailored for specific types of tasks with particular characteristics.⁸¹ Current AI technology tends not to be adaptable from one activity to other, unrelated activities. It is a mistake, for example, to assume that just because AI successfully beat a grandmaster in the game of Go—a famously difficult game—that that this same technology will necessarily lead to the automation of other difficult tasks, such as creative legal argumentation or problem solving.⁸² Different problem areas have different characteristics that make them more or less amenable to AI. Understanding the difference is the key to understanding the current (and near future) impact in law.

In short, current AI technology tends to work best for activities where there are underlying patterns, rules, definitive right answers, and semi-formal or formal structures that make up the process.⁸³ By contrast, AI tends to work poorly, or not at all, in areas that are conceptual, abstract, value-laden, open-ended, policy- or judgment-oriented; require common sense or intuition; involve persuasion or arbitrary conversation; or involve engagement with the meaning of real-world humanistic concepts, such as societal norms,

80. Elizabeth Gibney, *Self-Taught AI Is Best yet at Strategy Game Go*, NATURE (Oct. 18, 2017), <https://www.nature.com/news/self-taught-ai-is-best-yet-at-strategy-game-go-1.22858> [<https://perma.cc/442F-UDWU>].

81. Desai, *supra* note 20.

82. *Id.*

83. See James Vincent, *The State of AI in 2019*, VERGE (Jan. 28, 2019, 8:00 AM), <https://www.theverge.com/2019/1/28/18197520/ai-artificial-intelligence-machine-learning-computational-science> [<https://perma.cc/9JAB-8YLQ>].

social constructs, or social institutions.⁸⁴ Let's examine each of these tendencies in turn.

In general, AI tends to work well for tasks that have definite right-or-wrong answers, and clear, unambiguous rules.⁸⁵ For example, one reason that spam detection is susceptible to AI automation is that there are right-or-wrong answers in that domain: in general, a given e-mail either is spam, or it is not.⁸⁶ Chess is another example where AI has certainty about the state of the pieces on the board and right-or-wrong answers about desired results, such as the checkmate end-state.⁸⁷ Similarly, AI has been demonstrated to teach itself how to win at videogames.⁸⁸ Videogames, too, tend to have clear rules about what are examples of positive or negative behavior.⁸⁹

By contrast, many, if not most, problems in the real world do not exhibit such a dichotomous yes-or-no sets of objective answers. For example, a government decision to put a homeless shelter in one neighborhood versus another is not the type of problem that has an objective answer. Rather, it is the sort of public-policy issue open to subjective interpretation and involves subtle trade-offs and costs and balances among societal interests and members.⁹⁰ In short, to the

84. See RUSSELL & NORVIG, *supra* note 4, at 48–49; Michael Chui, James Manyika & Mehdi Miremadi, *What AI Can and Can't Do (yet) for Your Business*, MCKINSEY Q. (Jan. 2018), <https://www.mckinsey.com/business-functions/mckinsey-analytics/our-insights/what-ai-can-and-cant-do-yet-for-your-business> [<https://perma.cc/7HNW-7FCM>]; Jason Pontin, *Greedy, Brittle, Opaque, and Shallow: The Downsides to Deep Learning*, WIRED (Feb. 2, 2018, 8:00 AM), <https://www.wired.com/story/greedy-brittle-opaque-and-shallow-the-downsides-to-deep-learning/> [<https://perma.cc/9UKN-EXLC>]; Richard Waters, *Why We Are in Danger of Overestimating AI*, FIN. TIMES (Feb. 5, 2018), <https://www.ft.com/content/4367e34e-db72-11e7-9504-59efdb70e12f> [<https://perma.cc/R4WQ-QBEF>].

85. See Ed Oswald, *What Is Artificial Intelligence? Here's Everything You Need to Know*, DIGITAL TRENDS (Feb. 27, 2019, 11:30 AM), <https://www.digitaltrends.com/cool-tech/what-is-artificial-intelligence-ai/> [<https://perma.cc/9GAE-2NKC>].

86. Ben Dickson, *All the Important Games Artificial Intelligence Has Conquered*, TECHTALKS (July 2, 2018), <https://bdtechtalks.com/2018/07/02/ai-plays-chess-go-poker-video-games/> [<https://perma.cc/3SZB-DD89>]; Garry Kasparov, *There's No Shame in Losing to a Machine*, FORTUNE (Sept. 25, 2017), <http://fortune.com/2017/09/25/garry-kasparov-chess-strategy-artificial-intelligence-ai/> [<https://perma.cc/9TRZ-K394>].

87. Kasparov, *supra* note 86.

88. Dickson, *supra* note 86.

89. *Id.*

90. Frank L. Ruta, *Do the Benefits of Artificial Intelligence Outweigh the Risks?*, ECONOMIST (Sept. 10, 2018), <https://www.economist.com/open-future/2018/09/10/do-the-benefits-of-artificial-intelligence->

extent a problem area looks more like the latter—open-ended, value-laden, and subjective, without definite right-or-wrong answers—AI technology will tend to be much less useful.⁹¹

Second, AI tends to work well in situations where there are underlying patterns or structure that can be discovered in data or through knowledge representation.⁹² Again, e-mail spam detection offers a good example of a problem area with underlying patterns: e-mails that contain certain words such as “free” are from senders who you have not contacted before and are from certain known locations highly associated with spam e-mail. Similarly, language translation often works on the premise that certain similar words tend to appear in context together at a statistically higher rate than other unrelated words.⁹³ For instance, a word such as “king” might often appear in written texts close to related words such as “monarch” or “sovereign” at a statistically higher rate than other words. AI can harness a pattern like this to help identify words most likely to be associated with the meaning of “king.”⁹⁴ Similarly, many expert systems, such as medical-diagnostic systems, work by encoding medical tendencies about diagnostic symptoms particularly from domain experts, such as doctors.⁹⁵

By contrast, many other types of real-world problems do not necessarily have such clear underlying patterns that can be harnessed to produce useful results. For instance, if one is trying to write an original, persuasive essay on an arbitrary topic, it is not clear that there is a statistical pattern that one could ascertain in earlier texts to automatically produce such a compelling essay. Similarly, if one

outweigh-the-risks [https://perma.cc/F874-LRQN].

91. S. Abbas Raza, *The Values of Artificial Intelligence*, EDGE, https://www.edge.org/response-detail/26050 [https://perma.cc/R3YQ-MLE6] (last visited Mar. 26, 2019).

92. Bill Kleyman, *The Art of AI: Understanding Architecture and Use Cases*, DATA CTR. FRONTIER (July 25, 2018), https://datacenterfrontier.com/the-art-of-ai-understanding-architecture-and-use-cases/ [https://perma.cc/S428-NQUG].

93. Emma Wynne, *Artificial Intelligence: The Translator’s New Co-Worker*, MEDIUM (June 8, 2018), https://medium.com/datadriveninvestor/artificial-intelligence-the-translators-new-co-worker-4da86739cf7f [https://perma.cc/JD4D-XLQ6].

94. See generally Krupansky, *supra* note 19.

95. Fei Jiang et al., *Artificial Intelligence in Healthcare: Past, Present and Future*, 2 STROKE & VASCULAR NEUROLOGY 230, 230–31 (2017).

wanted to make a novel and interesting argument about philosophy, it is not clear that, aside from very broad patterns, one could mine texts for statistical patterns that could easily produce, in an automated way, such a useful, novel argument.

Another characteristic that makes a problem area amenable to AI relates to the ability to capture and encode relevant information. In the case of rules-based knowledge systems, the data that serves as the backbone of the AI system is often obtainable because it comes from people who are experts in the field of the problem.⁹⁶ For instance, if one is designing an expert system to help doctors diagnose diseases that asks questions about symptoms and that reasons about the likely diagnosis, the knowledge as to what questions to ask and what symptoms are relevant will come from working with domain experts—experts in the relevant field, such as doctors who are experts in the field of practice.⁹⁷ Similarly, if one is encoding an income-tax-based expert system such as TurboTax, one would gain the knowledge as to the relevant rules by working with lawyers, accountants, and other experts in the domain of tax code.⁹⁸

By contrast, for many problem areas there is no easy way to identify or capture the relevant knowledge. In some cases, key concepts or abstractions cannot be meaningfully encoded in a computer-understandable form. These problem areas will be less susceptible to automation through knowledge-representation-based AI approaches.⁹⁹

Other areas where AI tends to be successful involve problems where fast computation, search, or calculation provides a strong advantage over human capacity.¹⁰⁰ Chess, once again, provides a good example of AI providing an advantage.¹⁰¹ One of the reasons that automated chess systems routinely beat grandmasters is the ability of the automated systems to use their incredibly fast hardware

96. S.I. GASS ET AL., *supra* note 66, at 22.

97. *Id.*

98. *See id.*

99. *See id.*

100. RUSSELL & NORVIG, *supra* note 4, at 1.

101. *Id.*

to search through billions of possible chess positions to find those most likely to produce a positive result.¹⁰² Another example involves credit card fraud detection.¹⁰³ Although in principle, a human could manually inspect credit card transactions looking for signals of fraud, in practice, due to the billions of credit card transactions per day, this analysis by humans is impossible. Here, the advantage given by the incredible computing power of today's computer hardware, combined with machine learning's ability to automatically detect anomalies indicative of fraud, makes such a process amenable for automation with AI.¹⁰⁴ By contrast, for many other types of problems, raw computation provides little to no advantage over human-based analysis.

Finally, as mentioned, current AI technologies do not generally perform well, or at all, in problem areas that involve abstract concepts or ideas, such as "reasonableness" or "goodwill," that involve actually understanding the underlying meaning of words.¹⁰⁵ Similarly, these automated technologies tend not to do well in many problem areas that require common sense, judgment, or intuition.¹⁰⁶ Finally, the use of AI automation tends to be both ineffective and possibly inappropriate in many problem areas that are explicitly and fundamentally about public policy, are subjective interpretation, or involve social choices between contestable and differing value sets. Understanding these limitations will help us understand where current AI is potentially applicable and where it is less applicable in law.

II. *AI in Law*

Having described AI generally, it is time to turn to how AI is being used in law. At its heart, "AI and law" involves the application of

102. *Id.* at 29, 175–76.

103. See Krishna Krishnan, *Fraud Detection Using Artificial Intelligence in Payment Services and Credit Cards*, IDEAS2IT (Oct. 30, 2018), <https://www.ideas2it.com/blogs/ai-credit-card-fraud/> [https://perma.cc/ZY6D-5D8P].

104. See *id.*

105. See *supra* Section I.A.

106. See *supra* Section I.A.

computer and mathematical techniques to make law more understandable, manageable, useful, accessible, or predictable. With that conception, one might trace the origins of similar ideas back to Gottfried Leibniz in the 1600s.¹⁰⁷ Leibniz, the mathematician who famously co-invented calculus, was also trained as a lawyer and was one of the earliest to investigate how mathematical formalisms might improve the law.¹⁰⁸

More recently, since the mid-twentieth century, there has been an active history of researchers taking ideas from computer science and AI and applying them to law. This history of AI within law roughly parallels the wider arc of AI research more generally.¹⁰⁹ Like AI more broadly, AI applied to law largely began focused upon knowledge-representation and rules-based legal systems. Most of the research arose from university laboratories, with much of the activity based in Europe. From the 1970s through 1990s, many of the early AI-and-law projects focused upon formally modeling legal argument in computer-processable form and computationally modeling legislation and legal rules.¹¹⁰ Since at least 1987, the International Conference of Artificial Intelligence and Law (ICAIL) has held regular conferences showcasing these applications of AI techniques to law.¹¹¹

Pioneering researchers in the area of AI and law include Anne Gardner, L. Thorne McCarty, Kevin Ashley, Radboud Winkels, Market Sergot, Richard Susskind, Henry Prakken, Robert Kowalski, Trevor Bench-Capon, Edwina Rissland, Kincho Law, Karl Branting, Michael Genesereth, Roland Vogl, Bart Verheij, Guido Governatori,

107. See Giovanni Sartor, *A Treatise of Legal Philosophy and General Jurisprudence*, Vol. 5: Legal Reasoning 389-90 (Enrico Pattaro ed., Springer 2005).

108. *Id.*

109. Frans Coenen & Trevor Bench-Capon, *A Brief History of AI and Law*, U. LIVERPOOL (Dec. 12, 2017), http://cgi.csc.liv.ac.uk/~frans/KDD/Seminars/historyOfAIandLaw_2017-12-12.pdf [https://perma.cc/L77R-S52N].

110. Trevor Bench-Capon et al., *A History of AI and Law in 50 Papers: 25 Years of the International Conference on AI and Law*, 20 ARTIFICIAL INTELLIGENCE & L. 215, 277 (2012).

111. *ICAIL 2015—First Call for Papers*, INT’L ASS’N FOR ARTIFICIAL INTELLIGENCE (Sept. 10, 2014, 8:53 AM), <http://www.iaail.org/?q=article/icail-2015-first-call-papers> [https://perma.cc/92LD-6BAF].

Giovanni Sartor, Ronald Stamper, Carole Hafner, Layman Allen, and too many other excellent researchers to mention.¹¹²

But since about 2000, AI and law has turned away from knowledge-representation techniques toward machine-learning-based approaches, like the AI field more generally.¹¹³ Many of the more recent applications in AI and law have come from legal-technology startup companies using machine learning to make the law more efficient or effective in various ways.¹¹⁴ Other more advanced breakthroughs in AI and law have come from interdisciplinary university law-engineering research centers, such as Stanford University's CodeX Center for Legal Informatics.¹¹⁵ As a result of this private- and university-sector research, AI-enabled computer systems have slowly begun to make their way into various facets of the legal system.

One useful way of thinking about the use of AI within law today is to conceptually divide it into three categories of AI users: the administrators of law (i.e., those who create and apply the law, including government officials such as judges, legislators, administrative officials, and police), the practitioners of law (i.e., those who use AI in legal practice, primarily attorneys), and those who are governed by law (i.e., the people, businesses, and organizations that are governed by the law and use the law to achieve their ends). Let's examine each in turn.

A. *AI in the Practice of Law*

Attorneys—practitioners of law—perform multiple legal tasks, including counseling clients, gauging the strength of legal positions, avoiding risk, drafting contracts and other documents, pursuing litigation, and many other activities.¹¹⁶ Which of these tasks

112. *See generally id.*

113. *Id.* at 257.

114. Daniel L. Farris, *Top 5 Trends in Legal Tech and Privacy for 2019*, 25 WESTLAW J. CLASS ACTION 15, 15 (2018).

115. *See generally CodeX: Stanford Center for Legal Informatics*, STANFORD LAW SCHOOL, <https://law.stanford.edu/codex-the-stanford-center-for-legal-informatics/> (last visited May 11, 2019).

116. *Prelaw—What Do Lawyers Do?*, NALP, https://www.nalp.org/what_do_lawyers_do [<https://perma.cc/982D-APDZ>] (last visited Mar. 26, 2019).

traditionally performed by lawyers is subject to partial, or full, automation through the use of AI?

Some lessons as to where the use of AI in the practice of law may be headed and where it may be more limited can be gleaned from the example of litigation discovery and technology-assisted review. Litigation discovery is the process of obtaining evidence for a lawsuit.¹¹⁷ In modern business litigation, often this amounts to obtaining and reviewing large troves of documents turned over by the opposing counsel.¹¹⁸ Document review was traditionally a task performed by attorneys who would quickly read each document and indicate, often manually, whether a document was likely relevant or not to the legal issues at hand or perhaps protected by privilege.¹¹⁹

In the mid-2000s, with the advent of electronic discovery, so-called predictive coding and technology-assisted review became possible.¹²⁰ Predictive coding is the general name for a class of computer-based document-review techniques that aim to automatically distinguish between litigation-discovery documents that are likely to be relevant or irrelevant.¹²¹ More recently, these predictive-coding technologies have employed AI techniques, such as machine learning and knowledge representation, to help automate this activity.¹²² Some of the machine-learning e-discovery software can be “trained” on example documents: to teach the software to detect patterns for e-mails and other documents likely to be relevant to the scope of the litigation.¹²³ This automated-review software became necessary with the rise of e-discovery, as the document troves related to particular lawsuits began to rise into the hundreds of

117. Katharine Larson, *Discovery: Criminal and Civil? There's a Difference*, A.B.A. (Aug. 9, 2017), https://www.americanbar.org/groups/young_lawyers/publications/tyl/topics/criminal-law/discovery_criminal_and_civil_theres_difference/ [https://perma.cc/X6T2-F6SS].

118. *Id.*

119. *Id.*

120. Charles Yablon & Nick Landsman-Roos, *Predictive Coding: Emerging Questions and Concerns*, 64 S.C. L. REV. 633, 634, 637 (2013).

121. *Id.* at 637, 667–68.

122. *Id.* at 638.

123. *Id.* at 639.

thousands and sometimes millions of documents—well beyond human, manual capabilities.¹²⁴

It is important, however, to understand the limits of automated predictive coding. The computer typically does not have the last word on the relevance of documents. Human attorneys, at the end of the day, make the decision as to whether individual documents are or are not relevant to the case at hand and the law. The reason is that the computer software is simply not capable of making those decisions, which involve understanding the law and the facts and dealing with strategy, policy, and other abstractions that AI technology today is not good at dealing with.¹²⁵ Rather, we can think of automated predictive-coding systems as using patterns and heuristics to filter out documents that are very likely irrelevant to the case. Thus, rather than having human attorneys opine over a vast sea of likely irrelevant documents, the software is used to filter out the most irrelevant documents, to reserve the limited attorney-judgment time to that subset of documents that are much more likely to be relevant.¹²⁶ At the end of the day, it is still a person, not a computer, who is making the decision as to whether a document is helpful and relevant to the law and the case at hand. This is a great illustration of the way in which many sophisticated AI systems still require humans in the loop, as discussed above, and provides lessons of AI use in law more broadly. In areas of law or legal practice that involve judgment, human cognition will likely be difficult to replace given the current state of AI technology.

There is another key point to the litigation discovery example. It is exactly the type of task that that we would expect to be partially automatable using AI given its characteristics. Within many document troves, there are often clear, underlying heuristics that can be discerned by algorithms.¹²⁷ For instance, if one has a litigation

124. *Id.*

125. *Id.* at 637.

126. Yablon & Landsman-Roos, *supra* note 120, at 638.

127. *Demystifying Artificial Intelligence (AI)*, THOMSON REUTERS, <https://legal.thomsonreuters.com/en/insights/white-papers/demystifying-ai> [<https://perma.cc/S8PX-HA2V>] (last visited Mar. 27, 2019).

case involving sexual harassment, one can train the software to look for keywords that are likely to appear in harassing e-mails, or the system can use information that it has detected in previous harassment cases about words likely to appear in those e-mails. Many current AI approaches require problem areas that have underlying patterns or structures. Although that might apply to particular subsets of lawyering, such as document review, there are many lawyering tasks that involve abstraction, conceptualization, and other cognitive tasks that current AI technology is not good at.

There are other examples of machine learning being used in settings and in tasks that have traditionally been performed by lawyers. These examples include reviewing contracts *en masse* (for example, in a merger due diligence setting), helping to automatically put contracts and other legal documents together using AI (document assembly), and AI-assisted legal research.¹²⁸

An important point to emphasize is that these AI systems can quickly reach their limits. These technologies often just give a first rough pass at many lawyerly tasks, providing, for example, a template document for an attorney. In other cases, the software may merely highlight legal issues for a human attorney to be aware of.¹²⁹ By contrast, in more complex situations, ultimately the AI software typically does not create the final work product—such as a complete, written merger contract. Humans are still squarely in the loop for complex, sophisticated legal tasks. It is the part of lawyering that is *mechanical* and repetitive that is largely being automated.

Another interesting use of machine learning in the practice of law is in the prediction of legal outcomes.¹³⁰ One function that attorneys have traditionally done for clients is to weigh the strength of client arguments and the legal position of a client in a hypothetical or actual lawsuit.¹³¹ Increasingly, attorneys and others interested in the

128. *Id.*

129. Bernard Marr, *How AI and Machine Learning Are Transforming Law Firms and the Legal Sector*, FORBES (May 23, 2018, 12:29 AM), <https://www.forbes.com/sites/bernardmarr/2018/05/23/how-ai-and-machine-learning-are-transforming-law-firms-and-the-legal-sector/#6308a31c32c3> [<https://perma.cc/9HQ6-ZGTQ>].

130. *Id.*

131. *Id.*

outcome of legal cases are using machine-learning systems to make predictions about the outcome of cases and relying upon data, rather than instinct, to help assess their odds of winning a case.¹³²

In sum, lawyers today do a mix of tasks that run from the highly abstract to the routine and mechanical. Today's AI is much more likely to be able to automate a legal task only if there is some underlying structure or pattern that it can harness. By contrast, lawyerly tasks that involve abstract thinking, problem-solving, advocacy, client counseling, human emotional intelligence, policy analysis, and big picture strategy are unlikely to be subject to automation given the limits of today's AI technology.

B. AI Used in the Administration of Law

1. AI Used by Judges and Administrators in Decision-Making

Another facet of AI and law involves the use of AI in the administration of law.¹³³ Primarily, this involves government officials using systems that employ AI technology to make substantive legal or policy decisions.¹³⁴ A good example of this comes from the use of AI systems by judges in making sentencing or bail decisions for criminal defendants.¹³⁵ For example, when a judge is deciding whether to release a criminal defendant on bail pending trial, often she must make a risk assessment as to the danger of the defendant in terms of flight or reoffending.¹³⁶ Today, judges are increasingly using software systems that employ AI to provide a score that attempts to quantify a defendant's risk of reoffending.¹³⁷ These systems often employ machine-learning algorithms that use

132. *Id.*

133. *See generally* DANIELLE KEHL ET AL., ALGORITHMS IN THE CRIMINAL JUSTICE SYSTEM: ASSESSING THE USE OF RISK ASSESSMENTS IN SENTENCING (2017), https://dash.harvard.edu/bitstream/handle/1/33746041/2017-07_responsivecommunities_2.pdf?sequence=1&isAllowed=y [https://perma.cc/U6UC-8MCL] (analyzing and applying trends to the recent use of artificial intelligence in the courtroom).

134. *Id.* at 3.

135. *See, e.g., id.* at 2.

136. *Id.* at 13.

137. *Id.*

past crime data and attempt to extrapolate to make a prediction about the defendant before the judge.¹³⁸ Although the judge is not bound by these automated risk assessment scores, they are often influential in the judge's decisions.¹³⁹ This is an example of AI use in the administration of law by a government official.

Other examples of government systems that use AI arise in the area of various government benefits. Often, government agencies have programmed systems that contain a series of rules about when applicants for benefits should be approved for benefits and when they should not.¹⁴⁰ Typically, this is used as an efficiency measure to allow government employees to more quickly process applicants. However, it is important to emphasize that these systems often contain automated computer assessments that either entirely prescribe the outcome of the decision or, at the very least, influence it.

2. *AI Used in Policing*

Another significant use of AI in the administration of law comes in the policing context. Police have primarily used AI technology in two major contexts.¹⁴¹ The first aspect involves so-called predictive policing.¹⁴² This is the use of machine-learning technology to detect patterns from past crime data to attempt to predict the location and time of future crime attempts.¹⁴³ The police can then use this data to orient their resources and police presence in areas they believe to be most effective.¹⁴⁴ A second major use of AI in law enforcement

138. *Id.* at 10.

139. KEHL ET AL., *supra* note 133, at 13.

140. William D. Eggers et al., *AI-Augmented Government: Using Cognitive Technologies to Redesign Public Sector Work*, DELOITTE INSIGHTS (Apr. 26, 2017), <https://www2.deloitte.com/insights/us/en/focus/cognitive-technologies/artificial-intelligence-government.html> [https://perma.cc/4VLZ-8485].

141. See generally Odhran James McCarthy, *Turning the Tide on Crime with Predictive Policing*, OUR WORLD (Feb. 28, 2019), <https://ourworld.unu.edu/en/turning-the-tide-on-crime-with-predictive-policing> [https://perma.cc/5EVU-N26B].

142. *Id.*

143. *Id.*

144. *Id.*

comes in facial-recognition technology.¹⁴⁵ Police departments have routinely began to scan crowds or attempt to identify suspects by matching photo or video data with databases that contain photos of those who have previously come into contact with the government or law enforcement.¹⁴⁶

C. AI and “Users” of Law

A third category of AI involves users of law.¹⁴⁷ By users, I refer to the ordinary people, organizations, and companies that are governed by the law and use the tools of the law (e.g., contracts) to conduct their personal and business activities. A few AI-and-law uses are worth highlighting. First, many companies use business-logic policy systems to help them comply with the law.¹⁴⁸ These are essentially private expert systems that contain general, computer-based rules about company activities that are likely to comply, or not comply, with various governing regulations.¹⁴⁹ For instance, a company may have to deal with complex import/export regulations. To ensure compliance, they might model relevant laws using logic and knowledge-representation techniques to help their internal processes refrain from activities that would violate the relevant laws.

Another example of users employing AI in the use of law has to do with so-called computable contracts.¹⁵⁰ These are legal contracts that

145. Jyoti Gupta, *How AI Is Helping Industries with Facial Identification/Recognition*, CUSTOMERTHINK (Dec. 20, 2018), <http://customerthink.com/how-ai-is-helping-industries-with-facial-identification-recognition/> [https://perma.cc/9XBX-T5CM].

146. See Dakin Andone, *Police Used Facial Recognition to Identify the Capital Gazette Shooter. Here's How It Works*, CNN (June 29, 2018, 6:22 PM), <https://www.cnn.com/2018/06/29/us/facial-recognition-technology-law-enforcement/index.html> [https://perma.cc/D7JC-EVVJ].

147. See Jyoti Dabass & Bhupender Singh Dabass, *Scope of Artificial Intelligence in Law*, PREPRINTS (June 28, 2018, 3:13 PM), <https://www.preprints.org/manuscript/201806.0474/v1/download>, [https://perma.cc/L3X4-7MVW].

148. See *China's New Generation of Artificial Intelligence Development Plan*, FOUND. LAW & INT'L AFFAIRS: BLOG (July 30, 2017), <https://flia.org/notice-state-council-issuing-new-generation-artificial-intelligence-development-plan/> [https://perma.cc/SDF4-VGRA]; *Complying with Government Regulations*, KAUFFMAN ENTREPRENEURS (Nov. 10, 2005), <https://www.entrepreneurship.org/articles/2005/11/complying-with-government-regulations> [https://perma.cc/95DS-CXY5].

149. See Dorothy Leonard-Barton & John J. Sviokla, *Putting Expert Systems to Work*, HARV. BUS. REV., Mar.–Apr. 1988, at 91, 94.

150. See generally Harry Surden, *Computable Contracts*, 46 U.C. DAVIS L. REV. 629 (2012).

are expressed electronically and in which the meaning of the contract is expressed in computer-understandable form.¹⁵¹ A good example of this comes from many securities contracts in the finance industry where the trading contracts are expressed in computer-understandable form that allows the computer to automatically carry out the underlying trading logic behind the contract.

A final example of the use of AI in law involves so-called legal self-help systems.¹⁵² These are simple expert systems—often in the form of chatbots—that provide ordinary users with answers to basic legal questions.¹⁵³ A good example of this comes from the “Do Not Pay” app, which provides a basic legal expert system that allows users to navigate the legal system.¹⁵⁴

D. Contemporary Issues in AI and Law

Finally, there are a few important contemporary issues in AI and law worth highlighting. Although a fuller treatment is beyond the scope of this article, it is important to bring them to the attention of the reader. One of the most important contemporary issues has to do with the potential for bias in algorithmic decision-making.¹⁵⁵ If government officials are using machine learning or other AI models to make important decisions that affect people’s lives or liberties (e.g., criminal sentencing), it is important to determine whether the underlying computer models are treating people fairly and equally. Multiple critics have raised the possibility that computer models that learn patterns from data may be subtly biased against certain groups based upon biases embedded in that data.¹⁵⁶

151. *Id.* at 636.

152. Dominic Fracassa, *California Courts Look to Modernize with Chatbots, Video Tech*, S.F. CHRON. (May 14, 2017, 4:27 PM), <https://www.sfchronicle.com/business/article/California-courts-look-to-modernize-with-11143095.php> [<https://perma.cc/8SQ4-23QJ>].

153. *Id.*

154. Michael Kushner, *To Pay or Not to Pay: Free Legal Services at the Push of a Button*, JETLAW (Oct. 15, 2018), <http://www.jetlaw.org/2018/10/15/to-pay-or-not-to-pay-free-legal-services-at-the-push-of-a-button/> [<https://perma.cc/AG94-YR2A>].

155. See generally Omer Tene & Jules Polonetsky, *Taming the Golem: Challenges of Ethical Algorithmic Decision-Making*, 19 N.C. J. L. & TECH. 125 (2017).

156. *Id.* at 131–32.

For instance, imagine that software that uses machine learning to predict the risk of reoffending creates its predictive model based upon past police arrest records. Imagine further that police activity in a certain area is itself biased—for instance, perhaps the police tend to arrest certain ethnic minority groups at a disproportionately higher rate than nonminorities for the same offense. If that is the case, then the biased police activity will be subtly embedded in the recorded police arrest data. In turn, any machine-learning system that learns patterns from this data may subtly encode these biases.

Another contemporary issue with AI and the law has to do with the interpretability of AI systems and transparency around how AI systems are making their decisions. Often AI systems are designed in such a way that the underlying mechanism is not interpretable even by the programmers who created them. Various critics have raised concerns that AI systems that engage in decision-making should be explainable, interpretable, or at least transparent.¹⁵⁷ Others have advocated that the systems themselves be required to produce automated explanations as to why they came to the decision that they did.¹⁵⁸

A final issue has to do with potential problems with deference to automated computerized decision-making as AI becomes more ingrained in government administration. There is a concern that automated AI-enhanced decisions may disproportionately appear to be more neutral, objective, and accurate than they actually are.¹⁵⁹ For instance, if a judge receives an automated report that indicates that a defendant has a 80.2% chance of reoffending according to the machine-learning model, the prediction has the aura of mechanical infallibility and neutrality. The concern is that judges (and other

157. See generally Patrick Hall, *Predictive Modeling: Striking a Balance Between Accuracy and Interpretability*, O'REILLY (Feb. 11, 2016), <https://www.oreilly.com/ideas/predictive-modeling-striking-a-balance-between-accuracy-and-interpretability> [https://perma.cc/3GWQ-4TRB].

158. Luke James, *AI Is Useless Until It Learns How to Explain Itself*, TOWARDS DATA SCI. (Jan. 4, 2018), <https://towardsdatascience.com/ai-is-unless-until-it-learns-how-to-explain-itself-7884cca3ba26> [https://perma.cc/PK3D-FFUW].

159. Jason Tashea, *Courts Are Using AI to Sentence Criminals. That Must Stop Now*, WIRED (Apr. 17, 2017, 7:00 AM), <https://www.wired.com/2017/04/courts-using-ai-sentence-criminals-must-stop-now/> [https://perma.cc/YY84-437U].

government officials) may inappropriately defer to this false precision, failing to take into account the limits of the model, the uncertainties involved, the subjective decisions that went into the model's creation, and the fact that even if the model is accurate, still two times out of ten such a criminal defendant is not likely to reoffend.

CONCLUSION

The goal of this article was to provide a realistic, demystified view of AI and law. As it currently stands, AI is neither magic nor is it intelligent in the human-cognitive sense of the word. Rather, today's AI technology is able to produce intelligent results without intelligence by harnessing patterns, rules, and heuristic proxies that allow it to make useful decisions in certain, narrow contexts.

However, current AI technology has its limitations. Notably, it is not very good at dealing with abstractions, understanding meaning, transferring knowledge from one activity to another, and handling completely unstructured or open-ended tasks. Rather, most tasks where AI has proven successful (e.g., chess, credit card fraud, tumor detection) involve highly structured areas where there are clear right or wrong answers and strong underlying patterns that can be algorithmically detected. Knowing the strengths and limits of current AI technology is crucial to the understanding of AI within law. It helps us have a realistic understanding of where AI is likely to impact the practice and administration of law and, just as importantly, where it is not.